Reliability Modeling of Nuclear Power Plant Subsystems Using Statistical Flowgraphs

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NPPs play an important role in energy security and the reduction of airborne pollutants. As part of the DOE Light Water Reactor Sustainability Program, we are developing models to characterize the reliability and safety of NPP piping subsystems. Subsystems are represented as statistical flowgraphs, with nodes representing states of partial or complete failure, and edges representing probability distributions for transitions between states. Transitions are driven by processes based on the material properties of the pipes, and the physical and chemical dynamics of the fluid being carried. We describe a model for predicting cracking, leakage, and rupture of pipes, based on empirical failure data and stochastic differential equations for crack growth.

Nuclear power plants (NPP) produce about 20% of the total electric power used in the US, and nearly three-quarters of the power produced by non-carbon-emitting sources. Because of forecasted power demands and concern over carbon dioxide emissions, the Department of Energy (DOE) is funding research both on next-generation reactor designs [1] and on extending existing NPP operating life [2]. A key part of the DOE reactor sustainability program is Risk-Informed Safety Margin Characterization (RISMC), which requires statistical models for characterizing the reliability and safety of NPP subsystems.

We are working with collaborators at the INL, PNNL, and Electric Power Research Institute (EPRI) on modeling reliability in passive components of NPPs, specifically certain types of piping subsystems [3]. NPPs may have up to 40 miles of piping in various subsystems; many of these are safety-critical, such as reactor coolant piping and pipes supplying fuel to backup diesel generators. Pipes are subject to many failure mechanisms related to pressure, flow rate, and corrosion, which lead to cracking in the pipe walls, leakage, and ultimately rupture.

Figure 1 shows a Markov process model for piping failure [4]. From a state in which there is no detectable flaw (N) the system may evolve to a state D in which a non-visible flaw has been detected (e.g., by radiography), which may, in turn, lead to a visible leak. The flaw or leak states may lead to rupture of the pipe (state R), which is considered the failure state. In the flaw or leak states a repair can be done, restoring the system to its initial state. The process is represented as a statistical flowgraph [5], in which the graph edges are labeled with information specifying the probability distribution of time spent in the origin state before making a transition to the destination state. In this case, consistent with the assumptions of a Markov process, edge labels are constant transition rates, where, for example, the probability density of the waiting time T in state N prior to flaw detection is $\phi\exp(-\phi t)$.

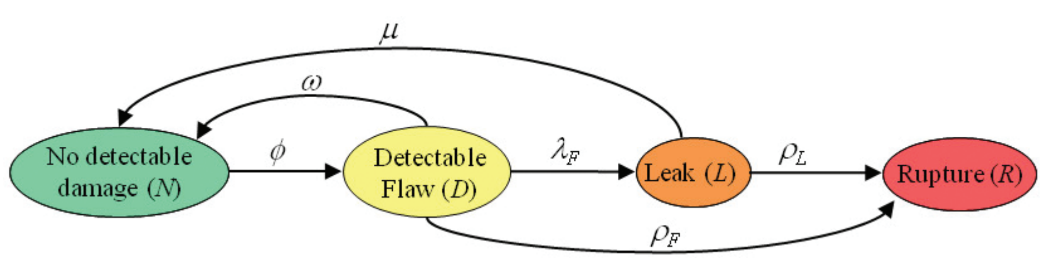

Fig. 1. Flowgraph model for pipe rupture.

Statistical flowgraphs are solved for quantities of interest by algebraic operations on integral transforms of the waiting-time distributions (e.g., Laplace or Fourier transforms) and analytical or numerical inversion of the resultant transforms. This yields results such as the probability distribution of the time for the first passage $N \rightarrow R$.

Where there is epistemic uncertainty regarding parameters such as ϕ, a Bayesian analysis may be performed by iterating the flowgraph solution over the joint posterior distribution of the parameters. The posterior is developed by assigning prior distributions to the parameters, which are then updated using observed data on transitions. This process allows quantification of the uncertainty in predictions, taking into account all parameter uncertainties; Fig. 2 shows an example, a plot of the posterior hazard rate for ruptures in a certain piping subsystem, with bounds indicating the 95% credible interval (the hazard rate $h(t)$ is the

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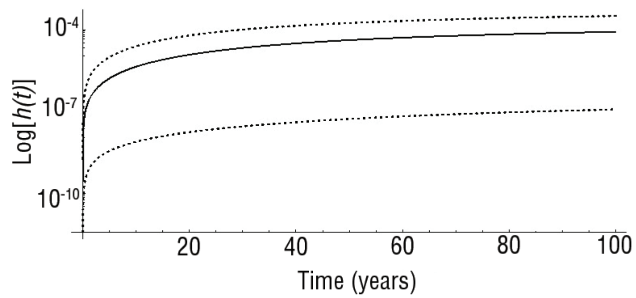

Fig. 2. Log plot of the posterior hazard rate for pipe rupture; 95% credible interval is dashed.

instantaneous failure rate at time *t*).

We have validated the Bayesian flowgraph methodology in the RISMC context, using the process in Fig. 1 as a benchmark [6]. The statistical flowgraph methodology also allows us to dispense with the restrictive assumption of constant failure rates, and model piping failures as semi-Markov processes (SMP) [7]. In an SMP, the waiting time in a given state may have an arbitrary distribution–for example, Weibull or lognormal, resulting in a much more flexible class of models.

RISMC modeling work to date has relied on field and experimental data, combined with expert judgment, to empirically derive probability distributions for waiting times in models such as Fig. 1. Thinking of this as a macro-model, micro-models for individual transitions, based on an understanding of the physical mechanisms involved, would also be valuable. For example, the $D \rightarrow L$ transition is a process of crack growth in the wall of the pipe, for which physical models and experimental data exist. The process of crack growth is stochastic, based on natural variation in material properties, applied stress, chemical environment, etc. Various methods exist for introducing randomness into deterministic physical models [8]; we are exploring stochastic differential equations (SDE) for this purpose. As a simple example, we might model the time-dependent crack length $a(t)$, using a log-linear model for the differential of crack length, with the SDE $\log da = \log \gamma + ½ \log a(t) + dW(t)$, where γ is a material constant and $W(t)$ is a Wiener process (Brownian motion) [9].

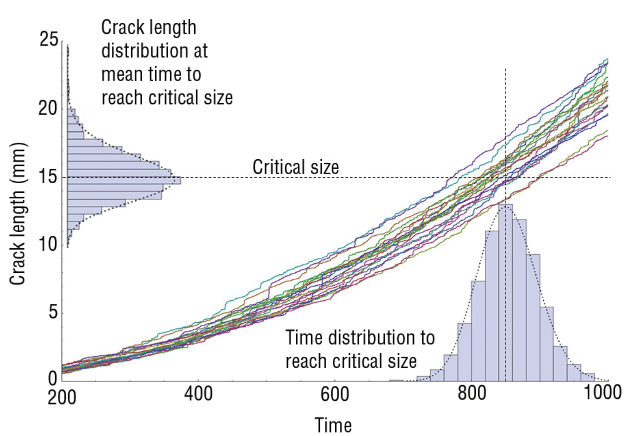

Fig. 3. Sample paths for crack growth given by numerical solutions of the SDE.

Figure 3 shows sample paths for crack growth generated by numerically solving this SDE [10]. The horizontal dashed line represents a critical crack length that will cause a leak. The histogram inset on the abscissa summarizes the time to reach the critical length based on a sample of 1,000 paths; the dotted line over the histogram is an inverse Gaussian probability density fitted to the sample data. The inverse Gaussian is plausible here since it is the first passage distribution for Brownian motion. This density can be used in the flowgraph macro-model as the waiting time density for the $D \rightarrow L$ transition. This is a simple notional example—much work remains to be done to develop models for various types of crack growth, and calibrate them using experimental data.

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